

Comparative Study on the Regulatory Effects of AI-Assisted Planting Strategies on Greenhouse Strawberry Production: Postprint

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Abstract

Artificial Intelligence (AI)-assisted cultivation contributes to enhancing the precision management level of protected horticultural crops and mitigating the increasingly prominent labor shortage issue. Strawberry is a typical labor-intensive horticultural crop; investigating and comparing the regulatory effects of different AI cultivation strategies and key technologies on strawberry greenhouse production can provide references for the improvement and industrial application of AI technology in horticultural crop cultivation. This study comparatively analyzed the regulatory effects of four distinct AI cultivation strategies on strawberry growth, development, yield, and quality, and examined the technical characteristics and existing challenges of AI cultivation with manual cultivation management as a benchmark. The results demonstrate that technologies including knowledge graphs, deep learning, visual recognition, crop models, and crop growth simulators each possess distinct advantages in strawberry AI cultivation. Specifically, the AI-1 group utilized knowledge graph technology to integrate expert experience, crop data, and environmental data, establishing a standardized strawberry cultivation knowledge framework and intelligent cultivation decision-making methodology, which yielded robust regulation of crop growth and development and achieved the highest output value with relatively low input. Compared to manual cultivation management, the AI cultivation strategy groups exhibited a 1.66-fold increase in average yield, a 1.82-fold increase in average output value, and a 1.27-fold improvement in the maximum input-output ratio. Aiming for high yield and superior quality, under greenhouse production conditions equipped with relatively comprehensive intelligent equipment and control components, AI-assisted cultivation can effectively enhance the precision of strawberry cultivation management and control, reduce water, fertilizer, and labor inputs, and generate higher returns, though challenges remain in simulating disturbances from manual management and acquiring crop ontological information.

Full Text

Preamble

Comparative Study of the Regulation Effects of Artificial Intelligence-Assisted Planting Strategies on Strawberry Production in Greenhouse

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Abstract: Artificial intelligence (AI)-assisted planting helps improve the precision management level of protected horticultural crops and alleviate the increasingly prominent labor shortage problem. Strawberry is a typical labor-intensive horticultural crop. Comparing the regulation effects of different planting strategies and key technologies on strawberry greenhouse production can provide references for technical improvement and industrial application of AI planting. This study compared and analyzed the regulation effects of AI planting strategies on strawberry growth, development, yield, and quality, and analyzed the technical characteristics and existing problems of AI planting using manual planting management as a reference. The results showed that knowledge graphs, deep learning, visual recognition, crop models, and crop growth simulators each have advantages in strawberry AI planting. Among them, the AI-1 group used knowledge graph technology to integrate expert experience, crop data, and environmental data, establishing a standardized strawberry planting knowledge structure and intelligent planting decision-making method. This approach achieved robust regulation of crop production and development, obtaining the highest output value with relatively low input. Compared with manual planting management, the average yield of the AI planting strategy group increased by 1.66 times, the average output value increased by 1.82 times, and the highest input-output ratio increased by 1.27 times. For the goal of high yield and high quality, under greenhouse production conditions equipped with relatively complete intelligent equipment and control components, AI-assisted planting can effectively improve the precision of strawberry planting management and control, reduce water, fertilizer, and labor input, and obtain higher returns. However, challenges remain in simulating disturbances from manual management and collecting crop ontological information.

Keywords: artificial intelligence; strawberry; planting strategy; regulation effect; automated greenhouse; knowledge graph

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Introduction

China is the world's largest strawberry producer and consumer, with annual production exceeding 3 million tons, accounting for more than 50% of global output [1]. In terms of production methods, Chinese strawberry cultivation has basically transitioned from traditional open-field cultivation to protected cultivation, with both semi-forcing and forcing cultivation accounting for significant proportions. Currently, strawberry greenhouses in southern production regions are gradually developing toward multi-span greenhouses, while new-generation solar greenhouses in northern regions are gradually replacing traditional solar greenhouses [2]. Along with improved facilities, technologies such as remote environmental monitoring and integrated water-fertilizer systems have become conventional configurations for strawberry protected production [1]. However, due to strawberries' short stature, large growth volume, disease susceptibility, and high requirements for temperature, humidity, and light, labor costs in production management are very high. Moreover, extensive cultivation management techniques and lack of standardized cultivation patterns often result in poor plant growth, numerous malformed fruits, severe diseases and pests, and production levels that still lag behind developed countries [3].

In recent years, artificial intelligence technologies such as machine learning and expert systems have accelerated research and application in agriculture, holding promise for improving precision management levels and alleviating labor shortages. As a typical representative of labor-intensive industries, strawberry production has an increasingly urgent need for intelligent technology applications.

The application of information technology in protected horticultural crop production management can be traced back to the 1980s, gradually evolving from traditional databases to decision support systems capable of solving complex problems [4]. Artificial intelligence has been extensively studied in crop disease identification, automatic irrigation, automated harvesting, and yield prediction. In recent years, AI technology has gradually developed and applied to strawberry planting, particularly with rapid progress in image recognition technology for disease and fruit identification. Deep network technologies, primarily Convolutional Neural Networks (CNN), demonstrate high efficiency in early disease identification, ensuring accurate classification of strawberry diseases [5-7]. The comprehensive application of YOLOv4, DCNN, and IoT-Edge technologies can effectively improve strawberry fruit recognition speed and reduce fruit damage caused by inaccurate positioning during mechanical harvesting [8-10]. AI-based remote crop management has also become a new research hotspot.

Greenhouse climate models and crop models simulate and predict greenhouse environments and crop growth, providing information on plant growth status under different conditions and environmental regulation information for achieving specific production goals, thereby supporting intelligent planting decisions. The combination of models and machine learning can achieve automated control of greenhouse crop production, which has been successfully validated for yield and quality regulation in crops such as cucumber, tomato, and sweet pepper [11-13]. However, the application of artificial intelligence in greenhouse crop production control remains limited, and research on overall strategies for strawberry intelligent planting and comprehensive regulation effects on strawberry production is rarely reported.

This study examined the technical selection and implementation effects of four different strawberry artificial intelligence (AI)-assisted planting strategies, using manual planting management as a reference to analyze the regulation effects of different AI planting strategies on strawberry production. The aim is to provide necessary references for strategy and technology selection in AI strawberry planting and to offer guidance for improving strawberry digital planting technology.

Materials and Methods

2.1 Experimental Environment

Experimental Location and Crop: The strawberry planting location was the National Plateau Cloud Fruit Industrial Park in Fumin County, Kunming City, Yunnan Province (25.2082°N, 102.5737°E). The strawberry cultivar “Akihime” was selected for its strong growth vigor, early fruiting, high fruit set rate, large fruit size, and high sugar content. From June 20 to July 19, 2020, plug seedlings underwent short-day photoperiod treatment for flower induction. Transplanting occurred on July 20, and harvest of three inflorescences was basically completed by the end of December. Compared with normal years, temperature and precipitation during the 2020 growing period were within normal ranges without significant fluctuations.

2.2 Greenhouse Structure and Equipment

This study included one AI planting strategy group and one control group. The AI planting strategy group comprised four AI planting treatments, designated as AI-1, AI-2, AI-3, and AI-4, with manual planting as the control group (CK). The AI planting strategy group used a glass solar greenhouse with an area of 96 m² (12 m × 8 m), equipped with intelligent control systems and environmental sensors from a Dutch company for fertilization, irrigation, window operation, ventilation, and shading, as well as environmental sensors to collect data on indoor and outdoor temperature and humidity, CO₂ concentration, wind speed,

wind direction, atmospheric pressure, light, and photosynthetic radiation. Plant growth image data were remotely collected through YSY cloud cameras with a lens resolution of 1920×1080 . The greenhouse contained six vertical cultivation troughs, with 100 strawberry plants per trough, using a mixture of peat and perlite (volume ratio 8:2) as the cultivation substrate. Additionally, the AI-2 treatment added photosynthetically active radiation sensors, stem diameter and leaf thickness sensors, and substrate moisture content and EC sensors. All these facilities and equipment could be automatically controlled and remotely operated.

The CK group used a traditional steel-frame arch greenhouse with an area of 96 m^2 ($12 \text{ m} \times 8 \text{ m}$), containing six ground-level cultivation troughs with 100 strawberry plants per trough and the same substrate as the AI strategy group. Supporting facilities included fans, shading nets, insect nets, water pumps, sulfur fumigators, drip irrigation hoses, proportional fertilization devices, thermohygrometers, EC meters, and pH meters. All facilities and equipment in the CK group required manual operation and could not be automatically or remotely controlled.

2.3 AI Planting Strategies

The basic workflow for strawberry planting management in the AI planting strategy group was consistent. Environmental sensors were used to monitor and collect real-time data on indoor and outdoor temperature, humidity, CO_2 concentration, substrate temperature, and EC values. Cameras collected real-time image information on crop growth, and the collected environmental and crop data were processed through the AI decision-making system. Combined with expert experience, production management decisions were formed, and then remote control and regulation of greenhouse environmental factors such as water, fertilizer, pesticides, light, temperature, and air were implemented through control components. On this basis, the four treatments in the AI planting strategy group adopted personalized AI planting strategies and technical protocols (Table 1).

Table 1 Artificial Intelligence Planting Strategy and Technical Protocols of Strawberry

Treatment	Technical Strategy and Implementation Process
AI-1	Knowledge Graph + Visual Recognition + Crop Model: Combined strawberry growth models and visual recognition to achieve greenhouse management decisions through knowledge reasoning [14] methods for optimal yield targets. First, the planting experience of 10 surveyed experts and environmental and crop sensor data were translated into computer language to construct a Neo4j-based strawberry planting management knowledge graph [15]. Then, crop water-fertilizer models and greenhouse climate models were used to analyze strawberry vegetative and reproductive growth processes, with path ranking algorithms [16] simulating expert decision-making based on the knowledge graph. Machine vision recognition focused on crop-derived data, using YOLOv4 neural network multi-feature fusion method [17] to identify strawberry growth stages, guttation conditions, inflorescences, and fruits. Growth deviations compared with potential crop growth status provided the basis for knowledge graph decision-making.
AI-2	Transfer Learning + Double-Layer Algorithm + Visual Recognition: Transferred the Dutch greenhouse tomato intelligent planting model [11, 18] to strawberry planting, developing intelligent planting management strategies through improved machine learning and conditional control algorithms, and introduced deep learning to process crop image information data for predicting and judging crop growth and development [12, 19]. A double-layer algorithm was adopted: the first layer was conditional decision-making, mainly setting thresholds based on expert experience to prevent extreme decisions from exceeding reasonable boundaries; the second layer was a hybrid decision combining yield prediction and setpoint optimization. Yield prediction was based on big data through machine learning, while setpoint optimization was based on traditional plant physiological models and expert experience.

Treatment	Technical Strategy and Implementation Process
AI-3	Crop Growth Simulator + WOFOST Model + Visual Recognition: Applied the crop growth simulator SUCROS87 [20] to strawberry potential yield prediction, calculating that under the experimental conditions, each strawberry plant could form a maximum of 1.6 g dry matter per day during peak fruiting, providing a reference for management regulation by comparing with actual dry matter. A WOFOST (World Food Studies) crop growth model [21] was constructed based on Specific Leaf Area (SLA) to predict strawberry yield, combined with visual recognition to compare potential and actual growth status, with expert systems providing planting strategies. A CNN-based image recognition system was built, achieving automatic single-leaf segmentation and leaf area calculation by adding residual modules to reduce interference from complex agricultural backgrounds.
AI-4	Model + Development Model: Constructed a strawberry growth and development model based on crop dry matter production and distribution patterns and the Product of Thermal Effectiveness and Photosynthesis Active Radiation (TEP) [22, 23] to predict and intervene in crop growth and yield formation. The strawberry dry matter production model mainly included leaf area index model, light interception model, and dry matter distribution index model for yield prediction under given water-fertilizer conditions. TEP parameter calculation was based primarily on relative thermal effectiveness of three base temperatures and photosynthetically active radiation. Through crop growth and development models, water and fertilizer at corresponding developmental stages were automatically controlled, and TEP parameters were adjusted according to actual crop growth status to delay or accelerate the growth process.

2.4 Crop Production Management Methods

Crop production management in the AI planting strategy group was divided into remote management and on-site management. Remote management referred to remotely operating greenhouse control components through the AI intelligent decision-making system to implement specific operations such as irrigation, fertilization, shading, supplemental lighting, and ventilation, intervening in greenhouse environment and crop growth. On-site management referred to auxiliary operations conducted manually, including removal of old leaves, flower thinning, fruit thinning, and fruit harvesting. The CK group used manual operations

for all production management, including opening/closing greenhouses, shading, water-fertilizer regulation, pest control, and flower/fruit thinning. When plants showed nutrient deficiency or stress, water-fertilizer ratios were adjusted based on planting experience to regulate pH and EC values. Plant protection and plant management in both AI and CK groups followed local general management measures [24]. Fruits from both groups were harvested at maturity using the same standards for yield and quality measurement.

2.5 Growth and Development Indicators Measurement

Every two weeks, changes in growth indicators such as stem diameter, leaf number, leaf length, and leaf width were measured and recorded for the AI planting strategy group. Plant shortened stem diameter was measured with a digital vernier caliper, leaf number was counted, and the length and width of the newest fully expanded leaf on each plant were measured with a ruler. Flowering times of the first, second, and third inflorescences were observed and recorded.

2.6 Yield Measurement

Yield was measured for strawberries harvested from the first and second inflorescences. Random sampling was used to determine yield, measured once per day. Continuous plant samples were randomly selected from the middle two cultivation troughs in each greenhouse. Harvested ripe fruits needed to meet single fruit weight $\geq 30\text{g}$, *regular shape, no pests or diseases, and have commercial value*. Yield evaluation was conducted through A ($\geq 30\text{ g}$), B (21-30 g), C (16-20 g), and D (10-15 g). Graded yield was calculated as the product of the average single fruit weight of each level and the total number of plants, with total yield being the sum of all graded yields.

2.7 Quality Measurement

Fruit sweetness was used as the quality indicator. After each harvest yield measurement, 10 fruits were randomly selected, cut transversely from the middle, and juice was extracted and dropped onto a portable spectrophotometer (model PAL-1, Atago Co., Tokyo, Japan) to measure soluble solids content. The average of 10 replicates was calculated as the fruit soluble solids content to characterize fruit sweetness.

2.8 Economic Analysis

Economic analysis quantitatively evaluated the input-output ratio and net benefit of each group, using only field data for accounting, excluding circulation costs. Total benefits were calculated based on graded and segmented prices from Yunnan wholesale market strawberry fresh fruit prices in previous years. Costs included fixed costs (greenhouse usage, facilities, and management) and production inputs (labor maintenance, basic pesticides, fertilizers, water and electricity, and additional facilities and production materials). Water and electricity prices were calculated at 5.6 yuan/m^3 and $0.5\text{ yuan}/(\text{kW}\cdot\text{h})$, respectively.

Since the AI strategy group entrusted expert teams for daily greenhouse management and maintenance, the required additional labor was calculated as a fixed cost. Pesticide and fertilizer inputs were accounted as fixed costs, with additional inputs calculated separately. Net profit was the difference between total benefits and fixed costs plus production inputs. The input-output ratio was the ratio of net profit to total investment.

Results and Analysis

3.1 Differences in Strawberry Growth and Development Among Different AI Planting Treatments

Stem Diameter: Stem diameter is an important indicator reflecting crop growth vigor. As shown in Figure 1 [Figure 1: see original paper], after transplanting, the stem diameter of AI-1 remained stable; AI-4 showed slow growth within 72 days after transplanting, then stabilized; AI-2 and AI-3 grew steadily within 59 days after transplanting, significantly decreased around 72 days when old leaves were removed, then recovered to rapid growth. From 17-59 days after transplanting, AI-4 stem diameter was significantly smaller than other treatments; after 72 days, AI-3 stem diameter was significantly smaller than other treatments.

Leaf Number: Leaves are the main organs for photosynthesis. Figure 2 [Figure 2: see original paper] shows dynamic changes in strawberry leaf number per plant from July 20 to mid-November. At 35 days after transplanting, average leaf number was concentrated around 4-5 leaves per plant, after which different dynamic changes emerged among groups. AI-1 showed smaller early increases, rapid increase after 80 days, peaking at 9.35 leaves per plant at 98 days, significantly higher than other groups. AI-2 had the highest leaf number before 56 days, dropping to around 4 leaves after old leaf removal at 66 days, then recovering quickly, with leaf number at 98 days second only to AI-1, with slight increases thereafter. AI-3 showed similar trends to AI-2 but had about one fewer leaf than AI-2 during the growing period. AI-4 showed continuous stable increase from 35 days after transplanting, with smaller fluctuations than other groups.

Leaf Length and Width: Leaf area directly affects photosynthesis intensity and is closely related to fruit yield. As shown in Figure 3 [Figure 3: see original paper], AI-2 leaf length and width increased rapidly after 16-31 days after transplanting, maintaining high values until 99 days, then fluctuating and decreasing. AI-1 showed similar trends to AI-2 but with smaller values. AI-3 leaf length and width increased rapidly after transplanting, peaking at 44 days, then continuously declining, remaining significantly lower than other groups after 77 days. AI-4 showed slow early leaf growth, rapid expansion after 58 days, peaking around 113 days, significantly higher than other groups.

3.2 Differences in Strawberry Flowering Period Among Different AI Planting Treatments

The timing and uniformity of strawberry inflorescence flowering partially reflect the regulation effects of AI planting strategies on the transition from vegetative to reproductive growth. Table 2 shows the distribution of flowering periods for the first, second, and third inflorescences. Most plants in AI-1, AI-2, and AI-3 completed first inflorescence flowering 27-43 days after transplanting, and second inflorescence flowering 74-104 days after transplanting, with concentrated flowering periods and longer intervals between inflorescences, showing good regulation effects. AI-4 delayed the first inflorescence by reducing greenhouse temperature and decreasing TEP, then accelerated growth by increasing TEP and water-fertilizer supply, causing the second and third inflorescences to be earlier than other treatments, resulting in short intervals and large overlaps between first and second inflorescence flowering periods.

3.3 Differences in Strawberry Harvest Period Among Different AI Planting Treatments

Strawberry fruit harvest period is closely related to flowering regulation effects. Table 3 shows the distribution of fruit harvest periods. Harvest periods for AI-1, AI-2, and AI-3 were basically concentrated 63-134 days after transplanting, with low yield during 74-104 days. AI-1 delayed fruit harvest through flowering regulation, with about 65.40% of fruits harvested 105-134 days after transplanting, and average single fruit weight increased from 13.30 g to 16.20 g. AI-2 had a relatively early harvest period, with the most fruits harvested 63-73 days after transplanting, accounting for 63.28% of total yield, but single fruit weight was significantly lower than other groups. AI-3 showed uniform fruit harvest distribution 63-134 days after transplanting. AI-4 first inflorescence fruit ripening was later than other three groups, concentrated 74-104 days after transplanting, with significantly higher average single fruit weight than other groups; second inflorescence fruits were concentrated 105-134 days after transplanting, with the lowest average single fruit weight among the four groups. This was mainly because this group delayed first inflorescence flowering, accumulated sufficient dry matter to increase single fruit weight, then accelerated growth by increasing TEP, causing the second inflorescence to be earlier. However, insufficient dry matter accumulation and overlapping fruit production periods between second and third inflorescences affected fruit development and maturity.

3.4 Analysis of Strawberry Yield and Quality Among Different AI Planting Treatments

From the perspective of commercial fruits harvested from the first and second inflorescences, the cumulative yield of the four AI planting strategy treatments was significantly higher than the CK group, with average yield 1.66 times higher than CK (Table 4). The average fruit sweetness of the CK group was 6.50% higher than the AI planting strategy group. The AI-1 treatment harvested 555

strawberries with total yield of 8456.10 g, with A-grade and B-grade fruits accounting for 21.65% and soluble solids content of 9.80%, outperforming the other three AI treatments in yield, high-grade fruit proportion, and sweetness. AI-2 had the lowest yield and highest proportion of low-grade fruits, with vigorous vegetative growth but low second inflorescence yield, indicating poor balance between vegetative and reproductive growth regulation. AI-3 yield was 7573.20 g, second only to AI-1, but D-grade fruits accounted for 73.72% with soluble solids content of 9.23%, the lowest among AI strategies, showing high yield without quality improvement. AI-4 yield was significantly lower than AI-1 and AI-3, with A-grade and B-grade fruits accounting for 8.70% and D-grade fruits 73.59%, showing low fruit uniformity, mainly due to weak early plant growth, low flowering uniformity, and adverse effects on yield formation.

3.5 Economic Analysis of Strawberry Production Among Different AI Planting Treatments

Economic analysis evaluated each group's input-output ratio and net benefit based on the output value from the first and second inflorescences (Table 5). Input costs for all four AI treatments were higher than CK, with average input costs 1.67 times those of CK. Compared with CK, AI strategy groups showed significant increases in facility investment (4.08 times) and water-electricity investment (1.32 times), but significant reductions in labor investment (69.20% of CK) and pesticide investment (83.28% of CK). Fertilizer investment varied significantly among AI groups, with AI-3 significantly lower than CK and AI-2 significantly higher than CK. Output values of all AI treatments were significantly greater than CK, with average output value 1.82 times higher. Input-output ratios of all AI treatments exceeded CK, with an average of 0.84. AI-1 achieved the highest input-output ratio of 1.09, 1.27 times higher than CK, while AI-2 had 0.61, lower than other AI treatments but higher than CK (0.48). AI-assisted strawberry planting showed characteristics of high input and high output, with AI-1 achieving the highest output value with relatively low input.

Discussion

Analysis of AI Planting Strategy Regulation Effects

Based on dynamic changes in stem and leaf indicators, AI-1 showed relatively robust plant growth regulation. This treatment comprehensively applied knowledge graphs and visual recognition, incorporating leaf guttation as an important indicator of crop water demand status into machine vision recognition, achieving effective collection and processing of crop data. Crop water-fertilizer models were used to timely adjust water-fertilizer supply, resulting in small stem diameter fluctuations, high leaf numbers, and relatively stable high leaf length and width values, conducive to producing more photosynthetic products. AI-2 mainly developed planting strategies through machine learning and con-

ditional control algorithms, regulating vegetative growth primarily to reduce stress, relying on crop models and expert opinions to avoid extreme decisions, with relatively high stem diameter, leaf number, leaf length, and leaf width indicators. However, the Dutch greenhouse tomato intelligent planting model could not completely match strawberry growth, causing large fluctuations in plant growth and development.

AI-3 used a CNN high-residual network image recognition system for efficient leaf area identification, regulating temperature and humidity accordingly. Plants showed vigorous early growth but weak later growth, which was not conducive to photosynthesis. The reason may be that the simplified crop growth simulator failed to simulate and predict crop nutrient demand, leading to decreased regulation precision in the later stage. AI-4 reduced environmental temperature through window ventilation and delayed growth stages by reducing TEP in the early stage, resulting in weak early stem diameter and leaf growth. In the middle and late stages, TEP parameters were adjusted according to growth status to accelerate plant growth stages, with relatively sufficient water and fertilizer supply, leading to stronger plant growth.

Applicability and Robustness of Crop Models

The applicability and robustness of crop models are crucial for precise plant growth regulation. AI-2 transferred the unlimited growth pattern of Dutch greenhouse tomatoes to strawberry planting, conducting intelligent decision-making through fusion of expert decisions and data-driven approaches. Early stages mainly relied on crop models and expert opinions, with later stages appropriately increasing the proportion of machine learning-generated decisions to partially compensate for traditional model mismatches. This treatment minimized stress through increased light and reduced window opening, with sufficient water-fertilizer supply ensuring good plant growth, relatively high stem diameter, leaf number, leaf length, and leaf width indicators, and relatively vigorous vegetative growth. However, during the second inflorescence flowering and fruiting period, both conditional decision expert experience and machine learning data accumulation in the double-layer algorithm were insufficient to form effective decisions, causing imbalance between vegetative and reproductive growth, affecting fruit set and maturity, and resulting in low final yield.

SUCROS87, as a universal simulator, is widely applied to simulate crop potential growth. Studies have found that the SUCROS87 simulator underestimates yield by 5%-25% [20], and its upgraded version can effectively reduce inaccuracies caused by parameter errors, showing good application in yield prediction for sorghum, pearl millet, and cotton. The regulation effect of AI-3 treatment showed that the SUCROS87 simulator can also be used for strawberry yield prediction, but its accuracy needs improvement. The crop model constructed based on specific leaf area is highly sensitive to small calculation and measurement errors of specific leaf area [25], and routine operations such as old leaf removal and flower/fruit thinning in strawberry plants also increase model prediction

errors. AI-3 treatment achieved intelligent regulation of greenhouse temperature and humidity through expert systems, with water-fertilizer management mainly adjusted weekly according to standard operating procedure parameters. Under this AI strategy, plants showed good early growth, but stem diameter, leaf number, and leaf length and width indicators during the second inflorescence flowering period were significantly lower than other groups, resulting in many fruits but low average single fruit weight, indicating that the simplified crop growth simulator could not simulate and predict nutrient demand, leading to significantly decreased regulation precision in the later growth stage.

Constructing crop models through TEP can effectively avoid the high sensitivity of the specific leaf area method to specific leaf area and the problem of destructive sampling measurement [26]. In this study, the development model constructed based on TEP by AI-4 treatment showed good performance in predicting strawberry growth stages, achieving a prediction error of about 7.87% for strawberry growth stages, and realizing remote control of production management through integration of growth and development models with the Internet of Things. This group aimed to improve fruit quality in the early stage by reducing light duration and window cooling to reduce TEP, supplemented by water-fertilizer regulation to delay inflorescence differentiation, resulting in weak early plant growth with stem diameter, leaf length, and leaf width significantly lower than other groups. In the later stage, growth stage was accelerated by increasing TEP, but leaf number was low, inflorescence flowering uniformity was poor, fruit harvest time was more dispersed than other groups, and overlapped with the third inflorescence flowering period. Although fruit number was high in late October, single fruit weight was low due to insufficient dry matter accumulation and conversion.

Conclusion and Implications

Conclusion

This study compared the regulation effects of four artificial intelligence-assisted planting strategies on strawberry production in greenhouses. From the implementation and results of the strawberry AI planting strategy group, under greenhouse production conditions equipped with relatively complete intelligent equipment and control components, AI regulation of environmental parameters achieved a certain degree of control over strawberry plant growth and development, flowering, fruit yield, and quality. Technologies such as knowledge graphs, deep learning, visual recognition, crop models, crop growth simulators, and expert systems can be combined and applied to AI-assisted strawberry planting. In this study, the AI-1 group, using knowledge graphs, growth models, and visual recognition as the main AI planting strategies, achieved optimal regulation of strawberry growth, development, yield, and quality.

Compared with traditional manual planting, AI-assisted decision-making can

effectively improve planting management precision and reduce water, fertilizer, pesticide, and labor inputs. The AI planting strategy group achieved an average yield increase of 1.66 times, average output value increase of 1.82 times, and maximum input-output ratio increase of 1.27 times.

Limitations and Implications of AI-Assisted Planting

The analysis of different AI strategy regulation effects in this study came from a single planting season, and strawberry yield and quality formation resulted from integrated regulation of multiple technologies, making it difficult to simultaneously reproduce the regulation effects of different AI strategies. However, the analysis results can still provide references for AI planting strategy formulation and key technology selection for strawberries and other horticultural crops.

None of the four AI strategy treatments achieved complete intelligent decision-making and control. First, operations such as transplanting, old leaf removal, flower thinning, fruit thinning, and harvesting required manual management. Second, management decisions for temperature, light, water, and fertilizer were only partially data-driven and partially based on expert experience. Although on-site manual management solved problems that intelligent decision-making management could not, it also created new issues. For example, after old leaf removal, significant disturbances to individual plants and populations increased simulation difficulty for growth models based on leaf area and plant dry matter distribution.

AI decision-making is essentially data-driven decision-making, but all AI strategy planting groups in this study faced data insufficiency problems. Environmental parameter collection was relatively comprehensive, but crop ontological information collection was difficult with small data volumes. One major reason is the lack of high-precision, real-time plant status sensors, making it difficult to achieve comprehensive monitoring of plant physical, chemical, and visual information [27]. The extraction and analysis of information on crop growth dynamics, yield traits, and quality traits are also difficult and require focused solutions for data-driven intelligent decision-making [28].

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